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AUDITORY PATTERN MEMORY

Mechanisms of Temporal Pattern Discrimination by Human Observers

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19. ABSTRACT (Continue on reverse if necessary and identify by block number) Several studies of temporal pattern perception were conducted using tasks where the listener discriminated whether two tonal sequences formed the same temporal pattern or which of two patterns was more rhythmic. In different conditions, the stimulus patterns were delayed, time expanded or compressed, presented at different frequencies and to different ears, or constructed of sub-patterns having different temporal correlations. Mathematical models of performance were employed to describe performance in these tasks. Further work was accomplished extending signal detection theory to the performance of statistically ideal and (certain) non-ideal groups. Other experiments were conducted on the processing of visual display elements as a function of element reliability and perceptual structure.					
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I. OBJECTIVES AND STATUS OF THE RESEARCH EFFORT

1. Perception of temporal patterns

A basic aspect of our normal perception of speech and music, is the ability to discriminate and categorize temporal patterns. We have been studying the discrimination of temporal patterns consisting of sequences of brief tones. The observer is presented with two sequences of tones and asked to report whether or not the two temporal patterns are the same--ignoring any other differences between the two stimuli, such as frequency. On half the trials, the patterns are the same, and on half they are different. For most of our experiments, the sequences were composed of 20-ms to 30-ms duration, 1000-Hz tones, and the mean intertone interval was set between 20 and 100-ms. The mean duration of a typical sequence was 600-ms and the time separation between the pair of sequences was 750-ms.

Subjects perform this task very well. The important variable controlling task difficulty is the correlation, p_{ex} , between the two series of tone interonset times. On SAME trials, p_{ex} is set to 1.0 and on DIFFERENT trials, p_{ex} is set to a constant value less than 1.0, depending on the condition of interest. The task is easiest when, on DIFFERENT TRIALS, p_{ex} is set to zero, and becomes more difficult as p_{ex} approaches one. The optimal way to perform this task is to estimate p_{ex} from the sequences of interonset times observed on a trial. We know how that statistic is distributed, and so we can compute how d' should depend on ρ and the number of tones in the sequence. We assume that there is an internal noise or jitter on the subject's estimate of the times, and we factor that into our prediction of subject performance. For our previously reported data, this jitter was approximately 15-ms.

a. Discrimination of arrhythmic tonal sequences: Effect of sequence onset delay. (Sorkin and Montgomery; revised manuscript under editorial review)

Sorkin and Montgomery (1991) showed that listeners could perform the discrimination task at a level that was well above chance, when uniform time compressions or expansions were made to one of the two patterns. All tones in their experiments were 1000 Hz; the sequences were presented monaurally and the time separation between the end of the first sequence and the beginning of the second sequence was approximately 800-ms. Performance decreased when the second sequence was compressed or expanded in time, and depended on the magnitude of the time transformation between the two sequences. The size of the decrease in performance ranged from 0 to 2 d' units over transformations of 0.6 to 1.6. The results supported the assumption that there was an internal noise proportional to the absolute magnitude of the transformation difference.

Additional evidence supporting the model and the relationship between temporal pattern discrimination and speech

recognition has been obtained with hearing impaired listeners using cochlear prostheses (Collins and Wakefield, 1992). Collins and Wakefield found that their observer's ability to discriminate temporal patterns depended on the temporal correlation between the two sequences, as predicted by the TC model. In addition, they reported that the observers' ability to discriminate arrhythmic sequences was positively correlated with the observers' speech recognition performance.

Data from comodulation masking release (CMR) and correlation discrimination experiments (CD) may support a different view of the pattern discrimination process. These experiments suggest that the listener performs a cross-band comparison of the amplitude envelopes of the waveforms. CMR is the reduction in the threshold for a signal masked by a narrow band of noise (the on-frequency band), that occurs when one adds a second band of noise (the flanking band) whose envelope is correlated with the first band (Hall et al., 1984; Cohen and Schubert, 1987).

In the CD task (Richards, 1987, 1988), subjects have to discriminate between simultaneously presented monaural noise stimuli that have partially correlated amplitude envelopes. In Richards' (1987) experiment, the stimuli were centered at 2500 and 2750 Hz and had bandwidths of 100 Hz. Richards' observers could discriminate between pairs of stimuli having different correlations between the noise envelopes. The observers' ability to discriminate was a function of the envelope correlation. Moore and Emmerich (1990) extended Richards' CD paradigm to conditions in which the signal duration, bandwidth, frequency separation, relative level, and center frequency of the lower band, were varied. Their results were consistent with a mechanism of envelope correlation. They reported that the effect of bandwidth and relative level on performance differed from that found in CMR tasks and they suggested that somewhat different mechanisms might be responsible.

The models proposed to describe the CMR phenomenon have been influenced by the waveform comparison models proposed to describe binaural masking level difference phenomena (Buus, 1985; Moore and Schooneveldt, 1990; Hall et al., 1988). CMR investigators also have been interested in the differential effects of monaural or diotic, and dichotic CMR presentations. Cohen and Schubert (1987) found that CMRs were slightly smaller in dichotic than monaural conditions, while diotic CMRs were greatest. Moore and Schooneveldt (1990) found dichotic CMRs somewhat greater than monaural CMRs.

These results from CMR and CD experiments, support the idea that listeners will be able to make temporal pattern discriminations across spectral (and spectral plus earphone) channels. They also suggest that these discriminations may be based on a mechanism of waveform envelope comparison, when the patterns are simultaneous or there is a brief delay between pattern onsets. If the pattern-onset time delay is longer than about 20-ms, the envelope correlation mechanism will fail,

possibly because of the system's inability to maintain an adequate memory for the stimulus. We extended the temporal sequence discrimination paradigm to conditions in which the two sequences were presented simultaneously or at brief time delays.

Figure 1 shows results from our experiments (Sorkin and Montgomery, submitted), in which we found that listeners can discriminate between two temporal patterns, even when the two patterns were defined by iso-frequency tone sequences presented at different frequencies (1000 and 2300 Hz) and to different ears. In the monaural condition, the second sequence began in the right earphone channel at a fixed time delay (intersequence interval) after the onset of the first sequence. The dichotic condition was identical except that the second sequence (at 2300 Hz) was presented in the left earphone channel. The circle symbols (solid lines) show performance in the monaural conditions and the square symbols (dashed lines) show performance in the dichotic conditions. The vertical bars are the average of the observers' standard errors of the mean. It is clear that there was very little difference between the monaural and dichotic stimulus presentation conditions.

The intersequence delay interval had a large effect on performance. Performance was good when the sequences were presented either at very short or very long time delays, and performance was poor at intermediate delays (when the sequences overlapped from about 40 to 90 percent). The results at very short intersequence intervals were consistent with CMR/CD results and with the predictions of both a temporal pattern correlation model and an envelope correlation model. The results at long intersequence intervals replicate our previous sequence discrimination results and support a temporal correlation interpretation.

In a second experiment, we temporally compressed or expanded all times in the second sequence. All marker tone durations and intertone gaps in the second sequence of tones were multiplied by a factor between 0.8 and 1.2 (chosen randomly on each trial). This manipulation was expected to affect the envelope comparison mechanism much more than the temporal pattern correlation mechanism. This is because temporal distortions cause temporal misalignment of the sequences; such misalignments result in a large decrease in the correlation between the envelopes of the sequence waveforms. The major effect of this compression-expansion manipulation was observed in the shortest interval conditions, where we had expected the envelope correlator mechanism to be active.

Figure 2 shows that performance decreased greatly when the intersequence interval was between 0 and 100-ms. The monaural no-compression and monaural-compression conditions are plotted together in figure 3; it is evident that the major effect of the time compression manipulation was for intersequence delays of less than 100-ms. These results support a two-mechanism interpretation: When the time interval between sequence onsets is

brief, the likely mechanism is envelope comparison. When the time interval between sequence onsets is long, the likely mechanism is temporal pattern correlation.

Why was discrimination performance so poor when the intersequence interval was greater than 50-ms and less than 350-ms? Since the envelope comparator cannot function effectively at these interval, the question reduces to asking why the temporal pattern correlator cannot function effectively in this region. We believe that the temporal pattern correlator cannot function when the sequences overlap in time. The attentional demands required by processing and encoding the sequence time interval information, may limit system operation to a single-channel mode. As a result, in order for the TC mechanism to function effectively, the stimuli have to be presented sequentially in time. This may be a general requirement for processing signals in the "context-coding" mode.

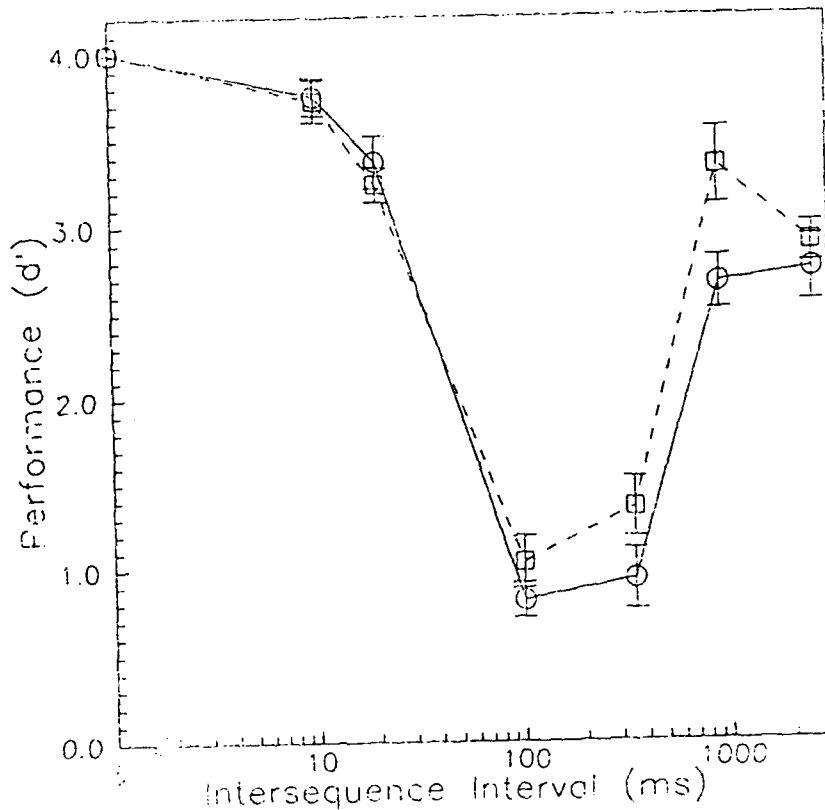


Figure 1. The average performance of four observers is plotted as a function of the time interval between the onsets of the first marker tone in each sequence. The circle symbols are the data for the monaural conditions and the square symbols are the data for the dichotic conditions. The brackets show the average standard error of the mean for the four listeners.

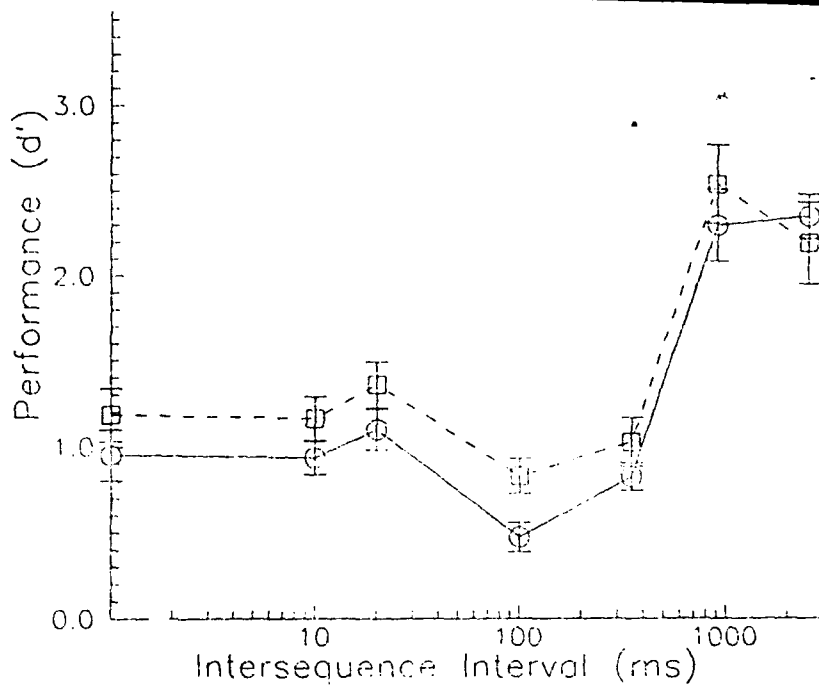


Figure 2. The average performance of four observers is plotted as a function of the time interval between the onsets of the first marker tone in each sequence; all times in the second sequence are compressed or expanded by a factor that varies randomly over trials. The circle symbols are the data for the monaural conditions and the square symbols are the data for the dichotic conditions. The brackets show the average standard error of the mean for the four listeners.

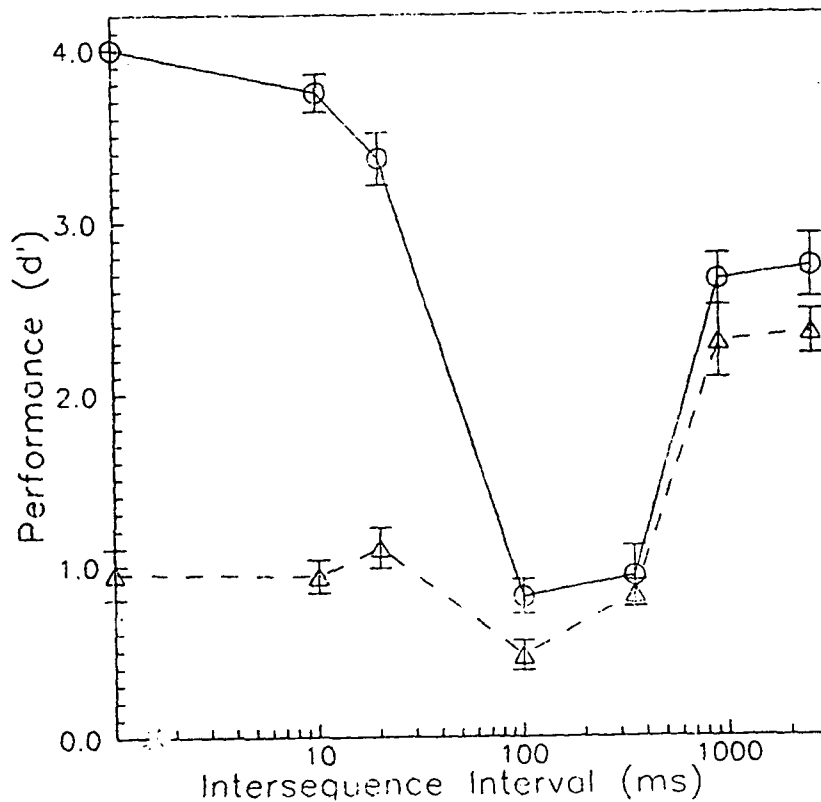


Figure 3. The average performance of four observers is plotted as a function of the time interval between the onsets of the first marker tone in each sequence. The circle symbols are the data for the monaural-no-time transformation condition, and the triangle symbols are the data for the monaural-random-time-transformation condition. The brackets show the average standard error of the mean for the four listeners.

b. Effects of rhythmicity on temporal pattern discrimination (Sorkin and Sadralodabai).

The rhythmic aspect of a stimulus is an important property of a temporal pattern. We have begun to analyze the effect of rhythmic properties on pattern discrimination, in the context of the TC model. Recently, we reported (Sadralodabai and Sorkin, 1992) on a preliminary study of the effect of rhythmicity on the discrimination of temporal patterns. Observers were presented with two sequences of 12 tones and asked to discriminate whether the two patterns were the same or different. The duration and the frequency of tones were 25 ms and 1000 Hz respectively. As in our other experiments, the temporal pattern of each sequence was determined by the intertone time intervals.

Two kinds of correlation were important in this experiment: One was the sequence correlation, ρ_{ex} , the correlation between the two 12-tone temporal patterns, as defined earlier. The second type of correlation, the rhythmic correlation, ρ_{rhy} , was defined as the correlation between the temporal patterns of successive 4-interval subsequences within the 12-tone sequence. We used ρ_{rhy} as a measure of the rhythmicity of the sequences. For example, a rhythmic correlation of 0 indicates no repetition of sub-patterns within a given sequence, and a correlation of 1 indicates complete repetition of the sub-patterns within a sequence.

The control condition in this experiment replicated the original correlation experiments, i.e., $\rho_{rhy}=0$, or no repetition within the sequences. Values of the sequence correlation were 0, 0.4, and 0.8. The mean and standard deviation of the intertone time intervals were 50 and 35 ms respectively. Performance (d') decreased as the sequence correlation increased, consistent with the earlier results. The TC model was fitted to this data and the internal noise was estimated for each listener based on their performance. Estimated values of σ_{in} for observers 1, 2, and 3, respectively, were 19-ms, 22-ms, and 19-ms.

We then tested performance in the experimental condition, with a rhythmic correlation, $\rho_{rhy}=1$. That is, there were 3 repetitions of the 4-interval subsequences within the sequence (the last repetition contained only three intervals). The sequence correlation was varied from 0 to .8, in steps of 0.2. As can be seen by the plotted points in figure 4, performance was very good and decreased as the sequence correlation increased.

We constructed a simple extension of the TC model to this task, using the following argument: Normally, there are two lists of 11 intertone times that may be used to estimate the correlation between the temporal patterns. When there are repeating patterns within the sequence, there will be fewer (independent) intervals are available for the correlation estimate. In the $\rho_{rhy}=1$ case, there are only 4 independent intertone time intervals, although this pattern of four intervals repeats 3 times. Thus, when the listener estimates the correlation in the $\rho_{rhy}=1$ case, only 4 intertone times may be used

instead of 11. This results in an increase in the variance of the estimate of the between-sequence correlation, and hence a potential decrease in performance. However, repeating the patterns within a sequence yields a reduction in the effect of the observer's internal noise, because the observer's estimates of the 4 intertone times within a repetition becomes (statistically) more reliable. Thus, according to the simple extension of the TC model: in the repetition condition the effective n is 4, rather than 11, and the effective internal noise (σ_{in}^2) is 1/3 of what it was in the non-repetition condition.

The model's predictions are shown as the smooth curves in figure 4. The improvement in performance due to the rhythmicity of the sequences was much better than predicted by the simple TC model. We also examined performance at rhythmic correlation values of 0, .5, 1, and at sequence correlations of 0 and .4. Most of the improvement in performance seemed to occur when the rhythmic correlation was greater than 0.5. Results at a mean intertone interval of 100-ms also were consistent with these results.

From these experiments, we conclude that the presence of rhythmicity plays an important role in a listener's ability to discriminate between two temporal patterns. Further experiments will attempt to revise the model so that it can capture the effects of rhythmic properties of the patterns. It appears that (when $\rho_{rhy}=0$) the observer may be using a non-optimum strategy for deciding if the sequences are different; that strategy results in an improvement in performance when there is information that reduces the size of the ensemble of possible sequences (e.g. when $\rho_{rhy}>0$). One possibility is to construct conditions for which $\rho_{t1,t2}$ is not an optimum strategy and in which the observer may use information about the possible sequences on a trial.

We have begun a series of experiments to directly assess the effect of important task variables on the discrimination of rhythmicity. We continue with our assumption that the rhythmicity of a pattern is related to the correlation between temporal units within the pattern (as defined by ρ_{rhy} in a pattern that has partially repetitive cycles of m subpatterns of size k , with a uniform correlation between cycles). The observer's task in our experiments, will be to discriminate which of two patterns is more rhythmic. Our initial experiments indicate that observer's have no trouble with this two-interval-forced-choice task, and that adaptive techniques provide reliable estimates of performance.

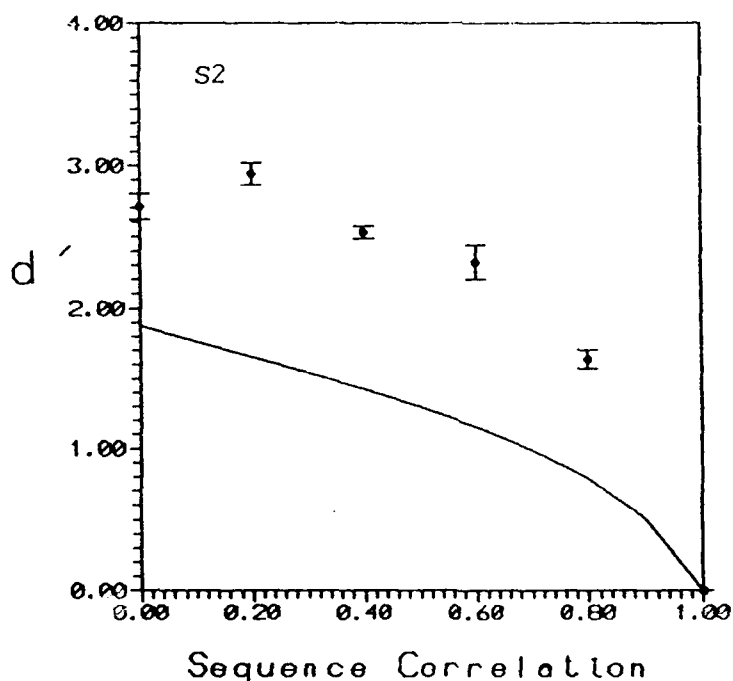
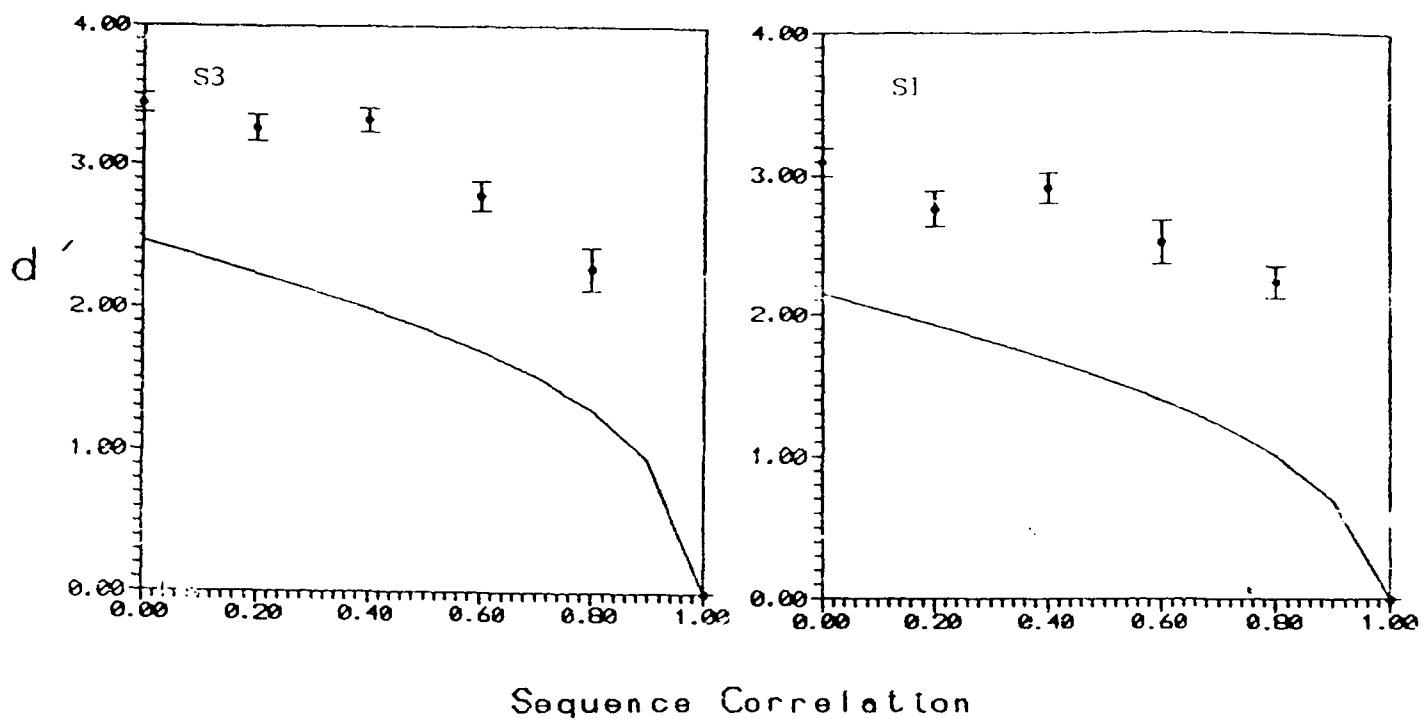


Figure 4. The performance of three observers in the $\rho_{rhy}=1$ condition (circle symbols). The brackets show plus and minus one standard error of the mean. The smooth curve is the performance of the observer based on the TC model using a value for the observer's internal noise that was estimated from performance in a separate $\rho_{rhy}=0$ condition.

c. Effect of temporal position and temporal context (Sorkin and Sadralodabai).

One weakness of the temporal correlation model is that it ignores effects occurring at different temporal or serial positions within the serial pattern. This insensitivity to time-position is a consequence of the assumption that pattern information is encoded independently of the location of that information within each sequence. Previous reviewers of our research have pointed out that this lack of sensitivity to conditional time-position properties may not be plausible, given what is known about speech and musical perception. For example, two patterns that have large and distinctive gaps near the end, and relatively uncorrelated patterns throughout the rest of their patterns, will probably be judged more similar than two patterns that have more uniform distributions of gaps, but a higher statistical similarity, i.e., temporal correlation (see Devenyi and Hirsh, 1975; Espinoza-Varas and Watson, 1986; Hirsh et al. 1990; and Watson et al. 1975, 1990). It is evident that a model that relies on a temporal correlation parameter that is uniformly defined over the pattern duration, probably will not be able to adequately specify the discriminability of the patterns.

To remedy this weakness of the TC model, we have begun to directly study the distribution of an observer's responses (different/same) as a function of both the position and the properties of the temporal intervals in the two stimulus sequences. This analysis is similar to those by Berg (1989, 1990), Berg and Green (1990), Lutfi (1989, 1990, 1992), and Sorkin et al. (1987), using the sample-discrimination procedure (see the description of weights analysis in section C). Although our procedure is not formally identical to the sample-discrimination procedure, these techniques will enable us to determine the differential weight employed by observers at different positions in the sequences.

On each trial, the observer's response and the sequence of intertone intervals in each sequence, will be recorded. We will compute a COSS-type function of the difference (and the product) of the corresponding intervals in each sequence. Specifically, we will compute the probability that the observer has responded 'different', conditional on the magnitude of the difference between the intertone intervals at that serial position, and conditional on the magnitude of the product of the intertone intervals at that serial position.

That is, for DIFFERENT trials, and across all values of $|t_{2,j} - t_{1,j}|$ for $j \neq i$, we will compute (for each position, i):

$$p(\text{respond "DIFFERENT"} \mid |t_{2,i} - t_{1,i}|) \quad (1)$$

and

$$p(\text{respond "DIFFERENT"} \mid t_{2,i} \cdot t_{1,i}) \quad (2)$$

We assume that the observer's decision on each trial is based on either

$$\sum a_i (|t_{2,i} - t_{1,i}|) \quad \text{or} \quad \sum a_i (t_{2,i} \cdot t_{1,i}). \quad (\text{The latter statistic}$$

is a version of the TC model.) We will use the standard deviation of the resulting distributions as an estimate of the observer's decision weight at position i . (The reader may wonder whether the properties of the resulting distributions can be used to determine which statistic was being used by the observer. From simulations, we know that the standard deviation of the difference and product distributions is approximately the same. Although the shape of the distributions are different, the number of trials required to tell which statistic was used probably is not feasible in a human experiment.)

These analyses will be repeated using sequences in which the intertone intervals have non-uniform means or non-uniform standard deviations, at different serial positions in the sequence. Sequences generated by the latter procedure will have serial positions that contain more information relevant to the task (in the sense of Lutfi's 1992 analysis and his Proportion of Total Variance hypothesis). Such positions should show higher observer weights than less variable intervals. We can also test whether the distinctiveness of the interval in the sequence, rather than its informativeness or serial position, commands higher observer attention. Sequences will be constructed in which the intervals in some serial positions have higher mean durations; these positions should show higher observer weights than the positions having shorter mean intervals, in the sense of Kidd and Watson's (1992) Proportion of Total Duration hypothesis. These experiments should provide specific, quantitative data on the effects of serial-context factors on temporal pattern discrimination.

Finally, the temporal pattern correlation model has not been tested with specific subsets of temporal patterns. For example, Povell and Essens (1985) and others have argued that there is a natural organization or structure to certain temporal sequences, depending on the relationship between the position of occurrence of the tones in the sequence and the basic sequence timing. Suppose that the duration of the base cycle of a repeating sequence is 760-ms, each containing 8 tones of 40-ms duration, and the smallest inter-tone gap is 40-ms. Any tone must start on one of the 16 possible starting times defined by those 40-ms (discrete) periods. Assume that all patterns have a tone at the first period. Certain sequences, by virtue of the specific starting times of the tones, will be perceptually more 'structured' than others. We will conduct pattern discrimination experiments with different subsets of these fully random sequences, using different algorithms for selecting the patterns, such as for metricity and nonmetricity. Using the Pattern Correlation model, we will evaluate the statistical and empirical aspects of these effects.

2. Analysis of Group Detection Systems

We have been using the theory of signal detectability to develop models for describing how groups of detection systems can detect signals. These models are based on the theory of signal detectability, specifically on multi-channel auditory detection (Berg, 1990; Green, 1992; Durlach et al., 1986). The models enable us to make quantitative predictions relating group signal detection performance (accuracy, d'_{group} ; bias, β_{group} ; and efficiency, η_{group}) to a group's size, the mean and variance of member d' , the correlation among member judgments, the relative influence of members on the decision, the group decision rule, and the degree of member interaction.

a. Analysis of the Ideal Group (Sorkin and Dai, submitted).

A simplified concept of the multi-channel detection/decision process is illustrated by the system shown in figure 5. This system is composed of a group of detectors which must decide whether a signal or no-signal event was present on a trial. Each detector monitors a distinct channel and each channel is subjected to several noise sources: One of these sources is unique to each detector (in the figure: n_1, n_2, n_3), and the other sources are common to two or more detectors (e.g. $n_{1,2,3}, n_{1,3}$). Each detector computes a statistic, X_i , that represents the detector's estimate of the likelihood that the signal was present on that trial. The list of estimates $\langle X_1, X_2, \dots, X_m \rangle$ is the group estimate vector, \mathbf{X} . The system's task is to decide, given the group estimate vector, whether or not a signal was present.

All the noise sources are assumed to be additive, normally distributed (Gaussian) random variables having zero means and variances of $\sigma_1^2, \sigma_2^2, \sigma_3^2, \sigma_{1,2,3}^2$ and $\sigma_{1,3}^2$; the magnitude of the variances are independent of which stimulus event occurred. Thus, the statistic, X_i , is a normally distributed (Gaussian) random variable, having a mean of zero on noise trials and a mean of μ_i on signal trials. The difference between the means of \mathbf{X} , given signal and given no-signal, is the mean vector, $\boldsymbol{\mu} = \langle \mu_1, \mu_2, \dots, \mu_m \rangle$.

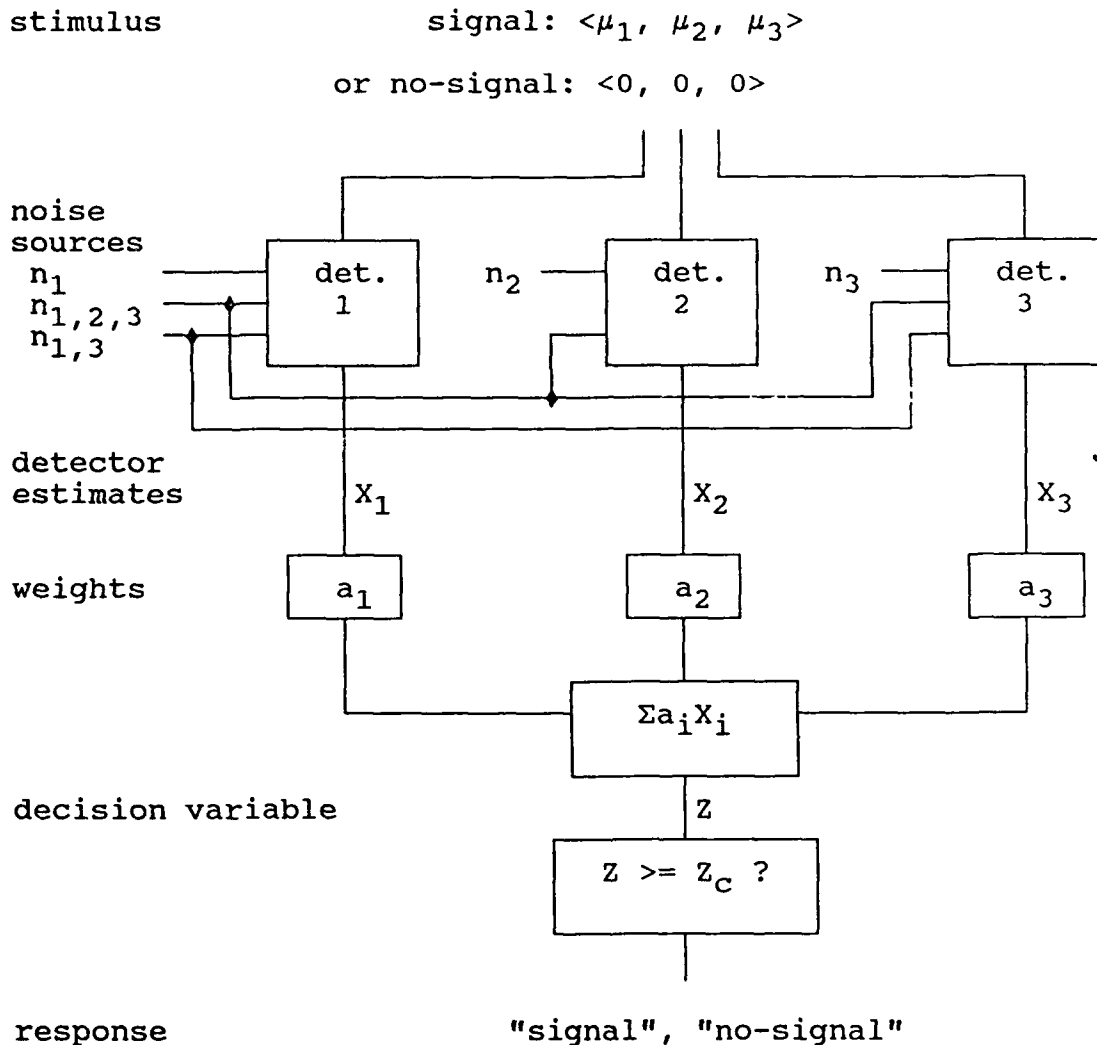
The variance of X_i is equal to the sum of the variance of its noise inputs. For detector 1 we have

$$\text{Var}(X_1) = \sigma_1^2 + \sigma_{1,2,3}^2 + \sigma_{1,3}^2 \quad (3)$$

The covariance of the estimates of any pair of detectors, $\text{Cov}(X_i, X_j)$, is equal to the sum of the variances of the noise sources common to those two detectors. For detectors 1 and 3:

$$\text{Cov}(X_1, X_3) = \sigma_{1,2,3}^2 + \sigma_{1,3}^2 \quad (4)$$

Figure 5. A simplified version of a group detection system. Each detector has a unique source of noise, plus a noise that is shared with one or both of the other detectors. The noise sources are independent, Gaussian random variables, with zero means and specified variances; the variances are independent of which stimulus event occurred. The decision variable, Z , is the weighted sum of the detector estimates.



The entries of the covariance matrix, Σ , summarize the values of these variances and covariances. For the **specific** system shown in figure 5, we have

$$\Sigma = \begin{bmatrix} \sigma_1^2 + \sigma_{1,2,3}^2 + \sigma_{1,3}^2 & \sigma_{1,2,3}^2 & \sigma_{1,2,3}^2 + \sigma_{1,3}^2 \\ \sigma_{1,2,3}^2 & \sigma_2^2 + \sigma_{1,2,3}^2 & \sigma_{1,2,3}^2 \\ \sigma_{1,2,3}^2 + \sigma_{1,3}^2 & \sigma_{1,2,3}^2 & \sigma_3^2 + \sigma_{1,2,3}^2 + \sigma_{1,3}^2 \end{bmatrix} \quad (5)$$

In the psychoacoustics literature, this detection task is framed as the problem of detecting a bandpass stimulus that has components in m channels, where the channels are defined in terms of spectral, spatial, or temporal dimensions. The multi-channel auditory signal detection problem has been discussed by Berg (1989, 1990), Berg and Green (1990), Durlach et al. (1986), and Green (1988, 1992). Note that the task also can be framed as a **group** detection problem, in which a **group** or **team** of detectors make the m observations and must arrive at a decision about the existence of signal. That is the focus of the proposed project.

An optimal detector employs a decision variable, Z , that is a monotonic function of the likelihood ratio statistic. As long as the covariance matrix has the same form for the signal and no-signal distributions, an optimal decision variable is a linearly weighted sum of the detector estimates (Ashby and Maddox, 1992), i.e.

$$Z = \mathbf{X}' \Sigma^{-1} \boldsymbol{\mu} + k \quad (6)$$

where \mathbf{X}' is a row vector, Σ^{-1} is the inverse of the covariance matrix, $\boldsymbol{\mu}$ is a column vector, and k is a constant. Let the vector, $\mathbf{a} = \Sigma^{-1} \boldsymbol{\mu}$, then an equivalent decision variable is

$$Z = \sum_{i=1}^m a_i X_i \quad (7)$$

where the a_i are optimal weights applied to the estimates, X_i . The optimal weights are expressed in terms of the inverse of the covariance matrix and the mean vector. The index of detectability, $d'_{\text{Ideal Group}}$, for this system is (Mahalanobis, 1931):

$$d'_{\text{Ideal Group}} = [\boldsymbol{\mu}' \Sigma^{-1} \boldsymbol{\mu}]^{\frac{1}{2}} \quad (8)$$

where $\boldsymbol{\mu}'$ is a row vector.

Suppose that two sources of noise enter each detector, one having a variance of σ_{com}^2 , which is common to all the detectors, and the other having a variance of σ_i^2 , which is unique to each detector. All of the off-diagonal elements of the covariance matrix are equal to σ_{com}^2 . The optimal weights, a_i , for this case are (Durlach et al., 1986):

$$a_i = \mu_i \left(\frac{1}{\sigma_i^2} - \frac{D}{\sigma_i^4} \right) - \sum_{j \neq i}^n \frac{D \mu_j}{\sigma_j^2 \sigma_i^2} \quad (9)$$

$$\text{where } D = \sigma_{\text{com}}^2 \left(1 + \sigma_{\text{com}}^2 \sum_{i=1}^m \frac{1}{\sigma_i^2} \right)^{-1} \quad (10)$$

The detectability index, d' , (Durlach et al., 1986) is:

$$d'_{\text{Ideal Group}} = \left[\sum_{i=1}^m \left(\frac{\mu_i}{\sigma_i^2} \right)^2 - D \left(\sum_{i=1}^m \frac{\mu_i}{\sigma_i^2} \right)^2 \right]^{\frac{1}{2}} \quad (11)$$

The equation can be simplified further by assuming that the unique variance components are equal in magnitude across the detector array, that is

$$\sigma_i^2 = \sigma_{\text{ind}}^2, \text{ for all } i \quad (12)$$

By definition, the correlation between any pair of detectors is given by:

$$r = \sigma_{\text{com}}^2 / (\sigma_{\text{ind}}^2 + \sigma_{\text{com}}^2) \quad (13)$$

Because the magnitude of the unique and common variances are uniform over the array of detectors, the detectabilities of the individual detectors, d'_i , are characterized only by the values of μ_i . We can normalize each detector's total variance by setting $\sigma_{\text{ind}}^2 + \sigma_{\text{com}}^2 = 1$, then

$$d'_i = \mu_i / (\sigma_{\text{ind}}^2 + \sigma_{\text{com}}^2)^{\frac{1}{2}} = \mu_i \quad (14)$$

Then we have the important relationship:

$$d'_{\text{Ideal Group}} = \left\{ \frac{m \text{Var}(d')}{1 - r} + \frac{m (\bar{d}')^2}{1 - r + mr} \right\}^{\frac{1}{2}} \quad (15)$$

where \bar{d}' is the mean of the individual d' 's, $\text{Var}(d')$ is the variance of the individual d' 's, m is the group size, and r is the inter-detector correlation.

b. Contingent criterion group (Sorkin and Crandall, submitted).

Groups vary in the degree of interaction among group members that occurs during deliberation. At one extreme is the hypothetical Ideal Group, in which it is assumed that members freely discuss all matters relevant to communicating the values of X_i and μ_i , and then put this information into a form appropriate for calculation of the optimum response. The other extreme is the group with no interaction among members; the members of this group simply make their private observations and then take a single vote. In between these two extremes are real groups such as committees, juries, and teams, where customs or formal rules dictate how group members communicate and how member judgments are combined to form the group decision.

One type of formally limited group interaction consists of an iterative series of ballots and discussions, such as occurs in an American jury. The group has a discussion, takes an open ballot consisting of the binary responses of each member, and counts the resulting votes. This sequence is repeated until a specified majority vote is reached, or until a time limit is exceeded.

In terms of detection theory, the group operates as follows: As a consequence of observing the stimulus evidence and prior to interaction as a group, each member makes an estimate, X_i , of the likelihood of signal. This estimate leads to a vote, R_i , of either signal, S, or no-signal, NS. The vote is based on the value of the member's observation, X_i , and the member's pre-deliberation criterion, c_i . The votes are tallied and, if unanimity is not reached, the group proceeds to discussion. During the discussion, each member acquires information about every other member's response, as well as about every other's detectability, d_i , and criterion, c_i . Each member then uses that information to compute a new criterion. Thus, each member shifts his or her own criterion as a function of the response (R_i), the estimated detectability (d_i), and the bias (c_i), of the other team members. After a new criterion is computed, the member's original observation, X_i , is again compared with it, and a new response is made. This process is repeated until a decision or time deadline is reached.

The rule for shifting a member's criterion follows from an analysis of aided detection described by Robinson and Sorkin (1985), Sorkin and Woods (1985), and Murrell (1977). An example of this system is the case of two detectors, one is a human detector and the other is an auxiliary "alarm" detector. These detectors operate together to perform a detection task. The human detector incorporates the binary response of the alarm detector to decide whether a signal or no-signal event has occurred.

According to Robinson and Sorkin (1985), the human detector incorporates the alarm detector's output by employing two different response criteria, depending on whether the alarm detector has responded signal (S) or no-signal (NS). These contingent criteria are computed using the following formula:

$$\beta(\text{given output } R \text{ from alarm detector}) = V \cdot \frac{p(\text{ns}) \cdot p(R|\text{ns})}{p(s) \cdot p(R|s)} \quad (16)$$

where $p(s)$ and $p(\text{ns})$ are the prior probabilities of signal and no-signal, respectively, and $p(R|s)$ and $p(R|\text{ns})$ are the probabilities that the alarm detector has made response R, given signal or given no-signal, respectively. V is the ratio of payoffs to the human detector for the four possible event outcomes:

$$V = [v(\text{NS} \cdot \text{ns}) - v(S \cdot \text{ns})] / [v(S \cdot s) - v(\text{NS} \cdot s)] \quad (17)$$

where $v(S \cdot s)$ is the payoff for correctly-decide-signal, $v(S \cdot \text{ns})$ is for incorrectly-decide-signal, $v(\text{NS} \cdot \text{ns})$ is correctly-decide-no-signal, and $v(\text{NS} \cdot s)$ is incorrectly-decide-no-signal.

Eq. 16 is based on the principle that the human detector should compute the posterior probability of S (and NS) given the alarm detector's response, and assumes that the human wishes to

maximize expected value. That is, after receiving information about the alarm response, the human detector updates her prior probability by substituting the posterior probability based on the alarm detector's response. This updated prior probability is employed in recalculating the human detector's criterion. Note that in order to calculate $p(R|s)$ and $p(R|ns)$, it is necessary for the human detector to know the d' and criterion of the alarm detector.

If there are m independent alarm detectors,

$$\beta = V \cdot \frac{p(ns)}{p(s)} \cdot \frac{p(R_1|ns)}{p(R_1|s)} \cdot \frac{p(R_2|ns)}{p(R_2|s)} \cdot \dots \cdot \frac{p(R_m|ns)}{p(R_m|s)} \quad (18)$$

where R_i is the response of alarm detector i .

The team situation is much more complex than the alarm detector paradigm because, (1) each detector's output goes to all the other detectors, (2) the system decision is based on the outputs of all of the detectors rather than just the one (the human's), and (3) the system decision is dynamic--the set of detector responses changes over time as each detector modifies its decision to accommodate the influence of the others.

We have implemented the contingent criterion group algorithm in simulations of team decision making. The most obvious group behavior produced by this algorithm is the tendency for the number of votes favoring the majority position to increase during deliberation. This occurs because a preponderance of say, S votes, shifts the average member's criterion toward making an S response. Responses from members having higher d 's produce more criterion shift than responses from less sensitive members, and a member's S vote that was made using a lax criterion for S counts less than one that was made using a very strict criterion.

We can summarize some qualitative aspects of the model simulations that we have run so far. First, on most trials the algorithm results in a decision toward the position initially favored by a majority of members. Second, sometimes members' criteria oscillate over successive ballots. Third, occasionally there is a reversal of the initial majority vote. Fourth, on occasional trials a decision is not reached by the time our arbitrary stopping point is reached. These qualitative aspects of the model's behavior during group deliberation are consistent with those found in previous empirical studies and simulations, for example, by Kalven and Zeisel's (1966) study of the American jury, and of small group studies described by Saks (1977) and Penrod and Hastie (1980).

In order to perform the criterion-shift calculations required by the contingent criterion model, each team member must know the vote, detectability, and criterion of each of the other members. In some groups, limitations on member communication prevent members from acquiring this information. One group of

this type is the Delphi Technique Group (Hastie, 1986; Gustafson et al., 1973), in which efforts are made to maintain the anonymity of members in order to prevent undue influence or the suppression of discussion by group members holding positions of authority. After balloting, each member is provided only with an aggregate vote that shows the number voting S and NS; no information is provided about individual d_i and c_i . It is easy to add such informational constraints to a limited interaction version of the contingent criterion model. Because specific information about the other members is not available, each member must use an average estimate for the sensitivity and criterion of the members giving the number of S and NS votes. Thus, calculations of $p(S|s)$ and $p(S|ns)$ are based on the group member's estimate of the average d' and criterion for the rest of the group. As in the Contingent Criterion case, a preponderance of S votes tends to shift members' criteria toward making an S response more likely.

Figure 6 illustrates the results of some simulations of different types of groups using different decision rules. The figure is a plot of group d' versus the size of the group. From best to worst performance, the different groups are: Ideal Group, Contingent Criterion Group-unanimous decision, Contingent Criterion Group-3/4 majority, Contingent Criterion Group-2/3 majority, Delphi group-2/3 majority, and Single Ballot-2/3 majority. All groups were assumed to have an inter-member correlation of 0, and the same distributions of member d' and β . Substantially the same results occur when the intermember correlation is greater than zero, but the differences are smaller.

We were concerned about use of the d' measure for characterizing the performance of these complex group detection systems. If the variance of the hypothesis distributions were not approximately equal, d' would not be an adequate measure, particularly for $\beta \ll 1$ or $\beta \gg 1$. Metz and Shen (1992) analyzed group detection without the requirement for the equal variance assumption. They predicted the accuracy gain in reading diagnostic images, such as X-films, that result from replicated readings by the same or different readers (all judgments were rated equally). Rather than computing a group d' , they showed how the parameters of the general binormal Receiver Operating Characteristic depend on the number of readings and the within-reader and between-reader variation.

To check on the equal variance assumption for our models, we plotted the group hit and false alarm probabilities that were obtained in several conditions of simulations using different values of mean β , on Receiver Operating Characteristic (ROC) curves [$P(S|s)$ versus $P(S|ns)$]. The resultant curves were quite similar to equal-variance, single-detector ROC curves. Thus, at least under the conditions evaluated by our simulations and proposed for the human experiments, the use of the d' and β measures appears to be appropriate for summarizing the performance of group systems.

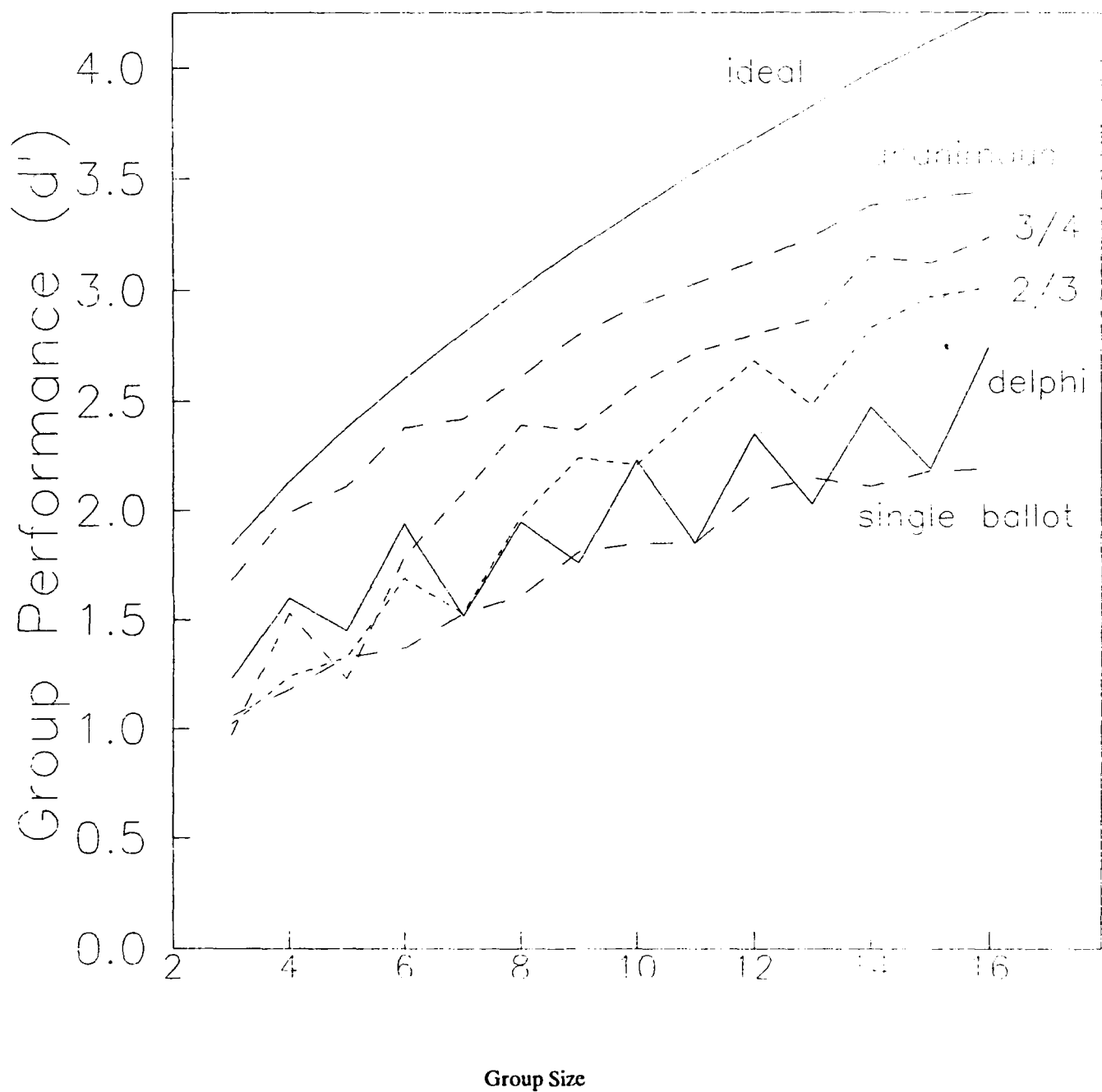


Figure 6. The performance of six different groups as a function of the group size. The group parameters are: $r=0$, $u_{d'i}=1$, $r_d=0.36$, $u_{crit}=1$, and $r_{crit}=1$.

3. Visual Display Processing.

In these experiments, we study an observers' ability to use multiple independent sources of visual information. The objective is to determine the observer's efficiency at using information from different spatial locations of the display. Observer sensitivity to different informational sources may be inferred from the decision weight that the observer assigns to a particular location in the visual field. A technique developed by Berg (1989; 1990) was used to estimate these weights.

a. Observer sensitivity to element reliability (Montgomery and Sorkin, submitted).

In our previous experiments (Sorkin et al., 1991), all display elements were equally informative, hence each element should have been weighed equally in the observers' decisions. When the observation durations were long, the weights were equal across the spatial array of display elements. However, when the observation durations were brief and the display coding was complex, the highest decision weights were associated with display elements in the center of the visual field, around the observer's fixation point. The weighting function was most highly peaked when performance was poorest. We concluded from these results, that under difficult conditions, the observer's allocation of attention was restricted to the central portion of the display.

This interaction between the difficulty of the task and the availability of information from different regions of the display is not surprising. A number of variables are known to affect an observer's ability to obtain information from the elements of a complex visual display. These include the number and spacing of items found in the visual field, the type of display code (Boles & Wickens, 1987; Legge, Gu & Luebker, 1989; Sanderson, Flach, Buttigieg, & Casey, 1989; Sorkin et. al., 1991), and the display item intensity (Eriksen & Rohrbaugh, 1970) and the time to completely sample the visual field (Burgess and Barlow, 1983).

When the stimulus durations in the Sorkin et al. (1991) experiment were long (more than 400 ms.), all display element weights were equal, indicating that the observers could process information from all regions of the display. Since the reliability of all the elements was also equal, an equal weight strategy was optimal for that task. An important question is whether, under similar duration and coding conditions, an observer can employ optimum weights when the reliabilities of the elements are not equal across the visual array. Obviously, the ability to match decision weights to the element reliability is necessary if the observer is to prioritize the display elements according to their importance to the task. In the present study we tested whether observers could use differences in the reliability of the display elements to make their detection decisions. We also wanted to determine whether using this information imposed a significant amount of additional processing "overhead" on the

observer.

On each trial of the experiment, observers were presented with a display consisting of nine display elements. The display elements were nine vertical line-graph gauges arranged in a horizontal array. The values displayed on the line-graph gauges, $\langle x_1, x_2, \dots, x_9 \rangle$, were determined by independent, normally distributed, random variables. On a signal trial, the values of the nine elements were selected from a distribution with a mean of μ_s and a standard deviation of σ . On a noise trial, the values were drawn from a distribution with a mean of μ_n and a standard deviation of σ , where $\mu_n < \mu_s$. The observer's task was to decide whether the data displayed had been generated from the signal or noise distribution.

The reliability of different display elements was controlled by manipulating the variance of the distributions from which the element values were sampled. There were two levels of element reliability; high reliability elements were sampled from distributions with lower variance than elements with low reliability. The variance of the nine display elements was the same for signal and noise trials, but differed across elements depending on the experimental condition.

The experiment included four different presentation conditions: stimulus duration (150, 400 and 800 ms), arrangement of source reliabilities (grouped or distributed over the spatial array), the manner in which trials of a particular condition were presented within a block (mixed or fixed), and whether or not the high reliability items were cued by a higher intensity (luminance cue). Figure 7 illustrates the results. The figure shows the observer weights for three subjects (and subject average) averaged over all high and low reliability elements, respectively, in the different conditions. The largest difference between the weights for the high and low reliability elements was for the luminance cue condition (URVL). These differences approached the ideal weight values. The next largest differences were for the condition when the spatial position of the different reliability elements were fixed within a block, and the smallest difference was when the spatial position varied and there was no luminance cue. There were no significant differences in weighting efficiency for different spatial arrangements. We intend to follow up on these results, with the hopes of optimizing the factors that enable the observer to use cues about element reliability.

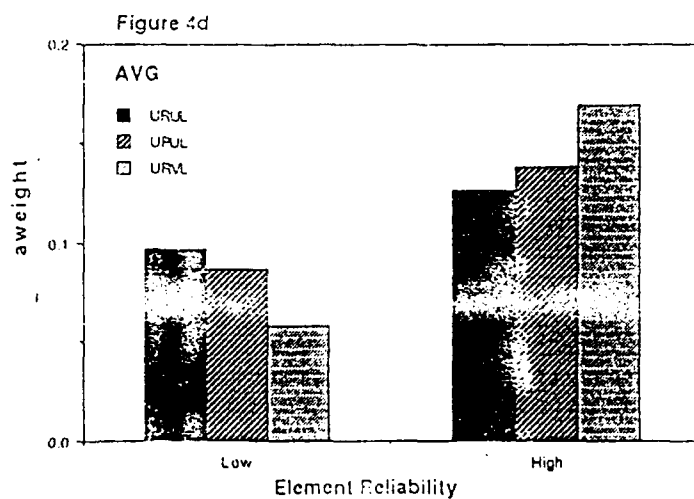
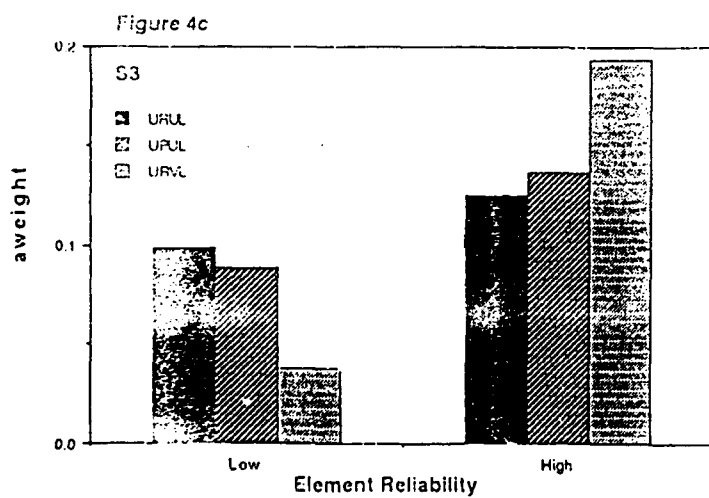
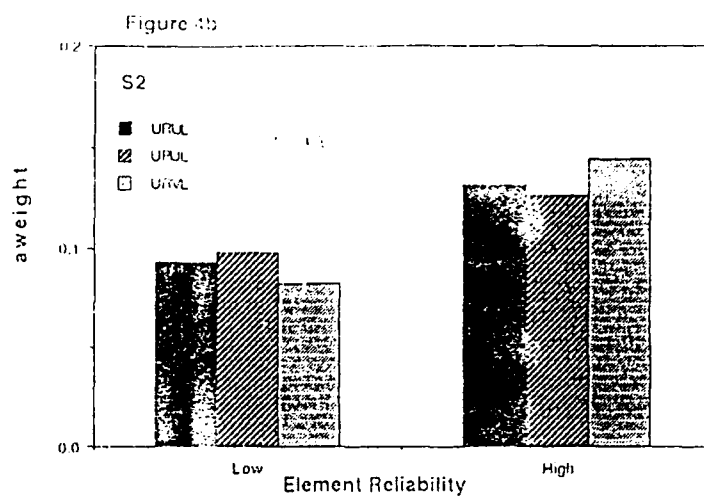
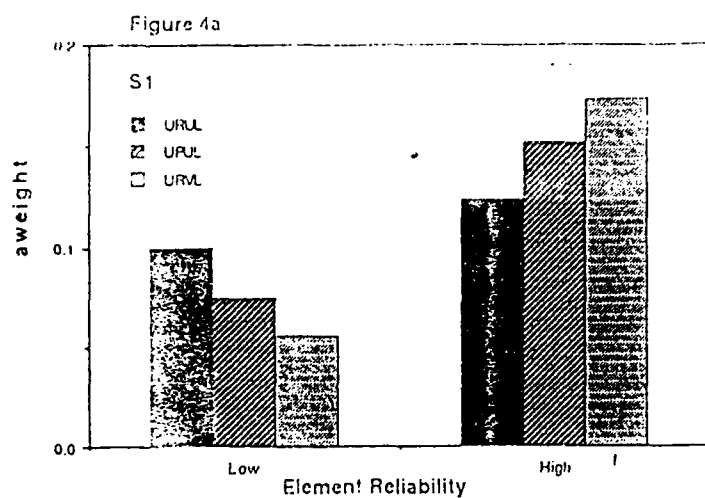


Figure 7. The average weights for high and low reliability elements for the three unequal reliability conditions (see text) at 800-ms duration. Graphs a-c are for observers S1, S2, and S3, and graph d is the averaged data.

6. Optimized Codes for visual display processing (Montgomery and Sorkin).

These experiments continue the study of observers' ability to use multiple independent visual information sources in forming a decision. The goal of this study is to identify means of coding the (independent) visual elements so as to maximize the efficiency of decision making. The information provided by a given source is a quantity that changes in magnitude depending on the underlying state, signal or noise. As with the previous study this quantity will be represented as a value on a graphical element in a visual display. We wish to examine the effects of two specific factors on an observer's ability to use the information conveyed by the separate elements. The first factor is whether or not the arrangement of elements produces an emergent, object-like feature. The second factor is the relationship between the emergent feature and the optimal decision statistic for the task.

Emergent features are perceptual properties that arise from the configuration of "simple" elements that are not identifiable in any given element (Treisman, 1986). For instance, if the elements are represented by three line segments, by arranging the elements in a particular fashion, we could create other features such as areas, angles and intersections, that are not observable in the individual lines. If we arranged the three line segments so as to create a figure with an enclosed contour, the emergent feature would have a distinct object-like quality.

There is evidence that a strong object-like feature can facilitate processing of the underlying elements. Some investigators have suggested that when elements are arranged to form a strong object-like feature, the emergent property is processed faster than the underlying elements (Pomerantz, 1981; Wickens and Andre, 1990) and may adversely affect the amount of resources allocated to processing the underlying elements. Wickens and Andre (1990) argue that such displays should be used only in tasks requiring information integration, rather than tasks requiring attention to be focussed on individual elements of the display. On the other hand, performance should be greatly abetted in a task where an emergent feature is directly related to the optimal decision statistic in the task. Unfortunately, there has been very little quantification of the relative role of these factors in different tasks.

In this ongoing study, observers are given one of two tasks to perform. In both tasks, the observers are given four independent pieces of information sampled from one of two distributions, **signal** or **noise**. One task (the integrated task) is a Yes-No detection task, similar to the equal reliability condition used in study a. In this case, each element is sampled from one of the two distributions, depending on the type of trial, and the observer has to use all four sources to decide whether the evidence is more representative of a signal or noise. The other task (the independent task) is a four-alternative

forced-choice (4AFC) task. Here, three elements are sampled from the noise distribution and one is sampled from the signal distribution. The observer has to decide which of the four sources represented the signal.

According to TSD, the optimal decision statistic is a likelihood ratio or some value that is monotonically related to the likelihood ratio. For the Yes-No task, the optimal decision statistic is the weighted sum of the evidence conveyed by the separate sources. For a 4AFC task, the decision statistic is the difference between a given weighted element and the weighted sum of the remaining sources. The source which has the greatest positive difference is the one selected as being the signal element. Table 1 depicts the conditions that will be run in the experiment. The columns represent the display code conditions. Each condition represents a display code that demonstrates some combination of the emergent feature properties described above. The four conditions consist of element arrangements which possess: (a) no emergent feature, (b) an non-object-like emergent feature that is mapped to the Yes/No decision statistic, ΣaX , (c) an object-like emergent feature that is not related to the Yes/No decision statistic, and (d) an object-like emergent feature that has a property related to the Yes/No decision statistic, ΣaX . Both the Yes-No and the 4AFC tasks are performed under each of these conditions, and are represented by the rows of the matrix in figure 1.

Table 1. Each observer will perform two tasks under four different display code conditions.

	No Emergent Feature	Related to ΣaX Non-Object	Not Related Object	Related to ΣaX Object
Yes/No Task				
4AFC Task				

If an object-like emergent feature facilitates the processing of the underlying elements, then we may find more efficient decision making performance for both Yes/No and 4AFC decision tasks when this feature is present. Alternatively, if processing of this object property interferes with processing of the underlying elements, then decision tasks which require sensitivity to the underlying elements may be hindered by display codes that possess this object property. Similarly, we should observe the effect of a relationship between the magnitude of a property of an emergent feature and the optimal decision statistic.

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II. PERSONNEL ASSOCIATED WITH THE RESEARCH PROJECT

Crandall, Christian S., Visiting Assistant Professor of Psychology, University of Kansas. Professor Crandall has been assisting with the group detection study.

Dai, Huanping, Assistant Research Scientist, Hearing Research Center, Department of Psychology. Dr. Dai has been assisting with the analysis of Ideal Groups.

Montgomery, D. A. (Widman). Graduate Student, Department of Psychology, University of Florida. Ms. Montgomery has been on the project since May, 1989. She expects to complete her Ph.D. in the Spring of 1993.

Sadrulodabai, Toktam. Graduate Student, Department of Psychology, University of Florida. Ms. Sadrulodabai joined the project in August, 1991, and has been working on the rhymicity experiments.

Sorkin, R. D. Principal Investigator, Professor of Psychology, University of Florida.

III. INTERACTIONS

Associate Editor, International Journal on Human-Computer Interaction.

Member and Chair, Acoustical Society of America Long Range Planning Committee.

Member, Research Advisory Council, Center for Applied Human Factors in Aviation, Orlando, Florida.

Invited lectures:

"Signal Detection Models of Group Decision Making", Department of Psychology, University of Central Florida, Orlando, FL, July 1992.

"Signal Detection Models of Group Decision Making", Central Florida Chapter of the Human Factors Society, Orlando, FL, July 1992.

Papers:

"Signal Detection Models of Group Decision Making", Florida Conference on Cognition, Gainesville, FL, April 1992.

"Signal Detection Models of Group Decision Making", MLD Conference, Bloomington, IN, July 1992.

Montgomery, D. A. and Sorkin, R. D. (1991). The effects of time stress on spatially selective operations. Paper presented at the 35th Annual Meeting of the Human Factors Society, San Francisco, CA, September, 1991.

Montgomery, D. A. and Sorkin, R. D. (1992). Observer sensitivity to element reliability in a multielement visual display. Paper presented at the 36th Annual Meeting of the Human Factors Society, Atlanta, GA, October, 1992.

Sadrulodabai, T. and Sorkin, R. D., Discrimination of tonal sequences composed of repeated temporal patterns. Journal of the Acoustical Society of America, 1992, 91, 2333.

Sorkin, R. D., and Dai, H. Group Decision Making: Analysis of the Ideal Group.

• • • IV. PUBLICATIONS

Sorkin, R. D. and Robinson, D. E. Computer-aided detection and classification. (in preparation).

Sorkin, R. D. and Montgomery, D. A. Effect of inter-sequence interval on the discrimination of tonal patterns. Journal of the Acoustical Society of America (under revised editorial review).

Sorkin, R. D. and Dai, H. Signal Detection Analysis of the Ideal Group. Organizational Behavior and Human Decision Processes (under editorial review).

Sorkin, R. D. and Crandall, C. S. A Signal Detection Model of the Jury. Psychological Review, (distributed for comments).

Montgomery, D. A. and Sorkin, R. D. Observer sensitivity to the source reliability in a multi-element visual display. Human Factors, (in preparation).